Full title: **Estimating day range from camera-trap data: the animals' behaviour as a key parameter**

Running title: Estimating day range from camera-traps

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Abstract

Day Range (DR), the distance travelled by an individual during the day, is an important metric in movement ecology. Moreover, DR is an important parameter for estimating population density through Random Encounter Model (REM). Traditionally, DR has been estimated applying GPS technology and considering straight-line distances between consecutive locations, which suppose an underestimation of the true path distance. In this work, we have tested the accuracy of a new approach based on camera-trap data for the estimation of DR when including animals' behaviour in the formulation. For that, we have considered wild boar (*Sus scrofa*) as model species. We tagged 18 individuals with telemetry devices and then monitored the population with camera-traps (photo and video mode) in order to estimate the DR. In the case of telemetry, a straight-line DR was estimated and rescaled with a tortuosity-related correction factor. Using this camera-trap data, we have revisited the procedure described by Rowcliffe *et al*. (2016) to estimate the DR. A new derivation of this approach was then developed, in which different animal behaviours were weighted to estimate the DR. There were no significant differences between the DR values obtained using telemetry data (corrected by the tortuosity-related correction factor) and those attained with the new approach. However, the original approach employed to estimate the DR based on camera-trap data underestimated this parameter. The DR estimated with the weighted approach is 12.74 $Km \cdot day^{-1}$ ± (SE) 1.89. Here, we showed that animals' behaviour should be weighted in order to estimate the DR when working with species that behave differently in front of the cameras. Our results described a new approach for estimating movement parameters without the need of capture and tagged individuals. These results can have a lot of relevance in movement ecology, disease dynamics, and population monitoring methods.

Keywords: Animal movement, population monitoring, Random Encounter Model, telemetry, tortuosity, wild boar.

1. Introduction

Obtaining accurate estimates of population density continues to be a constant challenge for wildlife management and conservation (Nichols & Williams, 2006). It is widely recognized that obtaining population size estimations is costly and that their reliability is usually not sufficient for management purposes, being necessary to consider other parameters related to body condition, vegetation effects, etc. (Morellet *et al.*, 2007). Some species are currently undergoing a notable expansion worldwide (e.g. wild boar *Sus scrofa*; Massei *et al*., 2015), whereas others are substantially declining in their entire distribution range (e.g. farmland birds; Inger *et al*., 2015). Feasible methods with which to attain precise and accurate estimations of population density are, therefore, in great demand in both scenarios. In this respect, the use of remotely triggered cameras (camera-traps, CT) for this purpose has substantially increased over the last few years (Rovero & Zimmermann, 2016). Even camera-traps can be detected by wildlife (Meek *et al*., 2014) is a method less intrusive than others, and most importantly, makes it possible to obtain information on highly cryptic species inhabiting a wide range of habitats (Steenweg *et al.*, 2017). CT are, therefore, now firmly established as a core tool for wildlife monitoring.

CT were traditionally used in wildlife monitoring in order to derive relative indices of population abundance (e.g. Massei *et al*., 2017). When population densities are the target parameter, CT are used to obtain data for capture-recapture methods (CR) and, more recently, spatially explicit approaches have been developed (Royle & Young, 2008; Jiménez *et al.*, 2017). However, the use of CR models (in a broad sense) requires marking individuals or working with individually recognisable species (but see spatial counts; Chandler & Royle, 2013). The use of these methods requires a greater effort than that of others. This is because it is necessary to make individuals recognisable for CT, since only a few species have a sufficient variability of natural marks for them to be individually recognisable. Rowcliffe *et al*. (2008) developed a method with which to estimate animal density using CT without individual recognition, the Random Encounter

Model (REM). The REM describes the rate of contact between animals and CT to estimate population density. For that requires trapping rate (i.e. the number of passages per unit of time), the day range (DR, i.e. the distance travelled by an individual in a day), mean group size and the radius and angle of the camera's field of detection. Although it is not as easy to estimate camera-related parameters as it is to consult model specifications (Rowcliffe *et al.*, 2011; Hofmeester, Rowcliffe & Jansen, 2017), the DR is the most costly and time-consuming parameter required for REM application (Rowcliffe *et al.*, 2012; Prichard *et al.*, 2014; Alexander & Maritz, 2015; Sennhenn-Reulen *et al.*, 2017; Nakashima, Fukasawa & Samejima, 2018). This signifies that, despite being a promising method for implementation in wildlife monitoring programmes, even on large spatial scales (Manzo *et al.*, 2012; Zero *et al.*, 2013; Anile *et al.*, 2014; Cusack *et al.*, 2015; Balestrieri *et al.*, 2016; Rademaker *et al.*, 2016; Caravaggi *et al.*, 2017; Gray, 2018), the application of REM is, at present, considerably limited by the estimation of the DR (Rovero & Marshall, 2009; Alexander & Maritz, 2015; Cusack *et al.*, 2015; Pfeffer *et al.*, 2017). Recently, Nakashima *et al.* (2018) described the Random Encounter and Staying Time (REST), an extension of the REM based on the amount of time that detected animals remain in the field of view of the CT rather than the DR; but no field trails have yet been undertaken to test the applicability of this method.

The DR has traditionally been estimated by employing intermittent location data, usually derived from telemetry studies (mainly using GPS devices), and then adding up the straight-line distances between consecutive locations in order to attain the total distance (Sennhenn-Reulen *et al.*, 2017; Tucker *et al.*, 2018). However, this approach underestimates the DR because the actual paths between consecutive relocations are not, in fact, straight (Laundre *et al.*, 1987; Reynolds & Laundre, 1990; Rowcliffe *et al.*, 2012; Sennhenn-Reulen *et al.*, 2017); animal paths are mostly tortuous (i.e. characterised by continuous turns). Estimates obtained from low sampling frequencies are, therefore, significantly shorter than those based on higher sampling frequencies. In order to manage these tortuosity-related problems, some authors have used more

intensive monitoring programmes with a higher frequency of relocations of tagged animals. This does not, however, solve the problem of tortuosity and other problems emerge, which are mainly related to fixed accuracy and battery life (Johnson & Ganskopp, 2008; Hurford, 2009; Dewhirst *et al.*, 2016); it is not really possible to register a complete track of tagged individuals with the current telemetry devices Dewhirst *et al*., 2016, Sennhenn-Reulen *et al*., 2017). Some authors have proposed tracking animals in the snow or the visual tracking of wild animals in parallel with a continuous GPS location series (Musiani, Okarma & Jędrzejewski, 1998; Sennhenn-Reulen *et al.*, 2017), but these approaches are limited to certain specific areas and species that are accustomed to human observers. Moreover, this approach is costly and time-consuming. In this context, various studies have verified correction factors with which to rescale the values obtained from intermittent fixed data to precise values of the DR and their applicability (Pépin *et al*. 2004; Rowcliffe *et al.,* 2012). Nevertheless, Rowcliffe *et al.* (2016) recently developed an approach with which to estimate the DR based solely on the information derived from CT. In this approach, the DR is estimated as the product of travel speed (i.e. average speed while active) and activity level (i.e. the proportion of the day that the population is active).

In this work we have considered the wild boar as a model species. The wild boar is widely distributed throughout Europe, with a high ecological and social relevance (Acevedo *et al.*, 2014; Massei *et al.*, 2015), particularly owing to its role as a reservoir of relevant shared diseases like tuberculosis or African Swine Fever (Gortazar *et al.*, 2012; Blome, Gabriel & Beer, 2013; Keuling *et al.*, 2018). Reliable estimates of population densities are needed for further risk assessment, essential to improve management strategies (Keuling *et al*., 2018). However, the methods traditionally employed to estimate wildlife population density are not reliable when working with this species owing to its behavioural peculiarities (but see Engeman *et al*., 2013). The nocturnal habits and elusive behaviour of the wild boar limited the applicability of those methods based on direct observation; and indirect methods, like pellets counts, are limited by the

estimations of other local-parameters such as defecation rates (Keuling *et al*., 2018). For all of the above, the REM can be a potentially feasible option (Chauvenet *et al*., 2017) once the method has been optimized, mostly as regards estimating the DR from CT data. Moreover, movement-related parameters can be essential for understanding and optimizing disease control efforts (Podgórski & Śmietanka, 2018)

While different approaches to derive DR values have been proposed, comparative studies in which the precision and accuracy of the estimations have been tested under field conditions are scarce. The aim of this study is to test a new approach for the estimation of the DR from CT using different categories of behaviour: feeding and moving. We hypothesized that for those species with marked behaviour could be necessary to weight the speed and activity values to finally estimate a DR value. Moreover, we are going to compare the DR estimations obtained with CT in photo and video mode. At this respect, we hypothesized that the estimations obtained in photo mode (using rapid-fire technology) can be similar to those obtained in video mode. These result could enhance the use of photo mode because of the advantages in relation to video (Glen *et al*., 2013; Rovero & Zimmermann, 2016; Steenweg *et al*., 2017).

2. Materials and methods

2.1. Study area

The study was carried out in the Doñana Biological Reserve (DBR), a territory of approximately 6800 ha located in Doñana National Park (DNP) (37°0'N, 6°30'W). DNP is a natural area covering 54000 ha located on the Atlantic coast of southwest Spain. As it is a protected area, neither hunting activities nor any management actions, such as artificial feeding or the provision of water for wild ungulates, are permitted.

2.2. Day range estimation

159 Eighteen wild boars were tagged with GPS-GPRS (Microsensory System, Sevilla,
160 Spain) collars in three different periods to estimate their DR. The population was also
161 monitored with CT during one of the telemetry study periods with the same purpose.
162 *2.2.1. Telemetry*
163 The animals were captured in different trapping areas throughout the DBR using five
164 padded foothold cage traps in order to collar a sample of animals from multiple social
165 groups. The animals were captured and managed following a protocol approved by the
166 Animal Experiment Committee of Castilla-La Mancha University and by the Spanish
167 Ethics Committee (PR-2015-03-08), designed and developed by scientists (B and C
168 animal experimentation categories) in accordance with EC Directive 86/609/EEC for
169 animal handling and experiments. The wild boar was anaesthetised following the
170 protocol described by Barasona *et al.* (2013), weighed, ear tagged, collared with GPS-
171 GPRS devices and assessed for body condition, age and sex. In those cases that more
172 than one individual was captured at the same time, we only collared one of them to avoid
173 pseudoreplication problems in telemetry data. The positional error associated with the
174 GPS locations was 12.08 m (SE = 0.20 m). The data collected included the date, time,
175 geographic coordinates and location acquisition time (LAT, ranges between 0–255 s).
176 Those GPS locations with LAT = 255 s were screened to detect and then remove
177 anomalous fixes (manufacturer's technical data). The locations obtained during the days
178 of collar deployment and of collar retrieval were discarded for the analysis to avoid
179 possible anomalous behaviour associated with handling procedures. .
180 Three independent study periods and sampling intensities have been considered in
181 this work. Nine adults (>24 months) wild boar (1 female and 8 males) were tagged
182 between December 2012 - March 2013 (period 1); with collars programmed to acquire
183 one location every hour (i.e. 24 locations·day^{-1}). Four adults wild boar (2 female and 2
184 males) were tagged between December 2015 - March 2016 (period 2); with collars
185 programmed to acquire one location every two hours (i.e. 12 locations·day^{-1}). Five adults
186 wild boar (3 females and 2 males) were tagged between January 2017 - March 2017

187 (period 3); with collars programmed to acquire one location every five minutes (i.e. 288
188 locations·day^{-1}). Inter-sex significant differences were not found in the movement rate of
189 the tagged individuals (linear model, Period 1-p:0.362; Period 2-p:0.655) and all
190 individuals were, therefore, pooled in the analyses (see below). The collars were
191 removed when animals died or were shot while the population control programme was
192 being carried out.
193
194 *2.2.2. Camera-traps*
195 The CT survey was carried out between January-February 2017 (period 3). We
196 designed a 1.5Km grid to guide the location of the 16 sampling points throughout the
197 DBR, covering all the habitats in the study area (Rowcliffe *et al.*, 2013) (Fig. 1). Two Little
198 Acorn cameras (Ltl-5310 Series LED IR Invisible) were placed at each point, without bait
199 (Rowcliffe *et al.*, 2016), one of them in photo mode and the other in video mode. The CT
200 were located within a buffer of 100m around the nodes of the grid in trees or man-made
201 poles. The motion sensitivity of all the cameras was set to high. The cameras were
202 deployed on the tree nearest to the computer-generated point, 30-50 cm above the
203 ground, with the angle of view parallel to the overall slope and unobstructed by
204 vegetation. If necessary, the vegetation in front of the camera was cut to reduce false
205 triggers resulting from its movement. The cameras were set to be operative all day, with
206 the use of an infrared flash at night, and the date and time of capture were automatically
207 stamped onto each image. The cameras were triggered by means of passive infrared
208 motion sensors and recorded a sequence of three consecutive photos or 30s-long video
209 clips. In order to record the individuals' trajectories in as much detail as possible, the
210 minimum time lapse between bursts was selected (1 second). The cameras were
211 checked every 10 days in order to change their batteries and SD cards, and to ensure
212 that they were functioning correctly.
213 Six markers (wooden sticks of 1m in length) were placed in front of the camera
214 forming an arc covering the angle of vision of the camera, three of them at 5m from the

camera, and the other three at 10m from the camera (Caravaggi *et al.*, 2016; Hofmeester *et al.*, 2017; see Fig. 2). After taking one photo of the structure, the sticks were removed. These marks were later used to locate the individuals captured with the cameras with a precision of 0.5m, and to estimate their travel speed. We have considered only those passages below a distance of 10m from the camera.

2.2.3. Approaches to derive DR

Telemetry: approach-1

The daily movement between consecutive locations was calculated using a programmed function in *R* 3.3.3 (Appendix 1). This was done by calculating the sum of the straight-line distances between consecutive fixes.

For periods 1 and 2, we have considered only those days with more than 80% of the fixed rate and a daily movement value was estimated for each day. For period 3, an average movement speed ($m \cdot s^{-1}$) was calculated for each hour of the day in order to subsequently obtain the daily mean speed. The daily speed ($m \cdot s^{-1}$) was then directly transformed into the DR ($Km \cdot day^{-1}$). This analytical procedure of pooling data per hour was adopted owing to the small number of days on which collars captured good fixes for the entire daily range. In the three periods, the DR values obtained directly from telemetry data were corrected using the tortuosity-related correction factor developed by Rowcliffe *et al.* (2012). The correction factor was calculated as the inverse value of the accuracy obtained, with the objective of rescaling the DR directly obtained from telemetry data to more accurate DR estimations. This correction was shown to be similar between species (see Fig.4 in Rowcliffe *et al*., 2012) with a relation between the body mass and the underestimation at a given sampling frequency. The correction factor increases as the sampling intensity decrease. For our data, we have considered the correction factor estimated for peccary (*Tayassu tajacu*), because this species is similar to wild boar in biological terms and as regards its body mass.

Camera-traps: approach-2 & approach-3

The procedure by which to estimate the DR from information obtained from CT described by Rowcliffe *et al.,* (2016) was then applied. In this method, travel speed is estimated using the photos/videos of the animals captured by the CT. This is done by dividing the distance travelled by the duration of the sequence (difference in time between the time stamps on the first and last picture/photogram). As suggested by Rowcliffe *et al*. (2016), those sequences in which animals reacted to the camera were discarded. However, animals are more likely to make contact with cameras when they move faster (Hutchinson & Waser, 2007). This problem was solved by fitting log-normal and Weibull distribution models in order to estimate the average travel speed (Rowcliffe *et al.*, 2016); the most parsimonious models were selected using AIC.

Camera-traps only detect animals when they are outside their refuges (i.e. active animals) and it is, therefore, necessary to take into account the population's activity rate. The data obtained from the CT were also employed to estimate activity (Rowcliffe *et al.,* 2014). This procedure is based on the key assumption that all the individuals in the population being sampled are active at the peak of the trap rate, and the trap rate at a given time of day is, therefore, proportional to the population's level of activity. The activity index per day was estimated using the 'activity' R package (Rowcliffe, 2016). In approach-2, the DR was, therefore, estimated as the product of the activity index (a) and averaged travel speed (s).

However, wild boars were recorded by the CT with two marked different behaviours. The behaviours observed with the cameras can be classified in two categories with quite different movement speeds: i) feeding and, therefore, slow movements, and ii) moving among habitats and, therefore, rapid movements. The general activity value was multiplied by the percentage of sequences of each type of behaviour to obtain an activity value for each of them. This consequently led us to describe a new procedure, approach-3, in which independent activity indices (a_i) and travel speeds (s_i) are estimated for each behaviour and, therefore, in this case, DR = ($a_{feed} \cdot s_{feed}$) + ($a_{move} \cdot s_{move}$).

Approaches 2 and 3 were applied in this study using the data obtained from both photos (approaches 2.1 and 3.1, respectively) and videos (approaches 2.2 and 3.2, respectively). The standard error in these approaches was estimated by means of Goodman´s (1960) variance of product formula.

The DR values obtained using the different approaches were then statistically compared using the Wald test, with a test statistic W assessed on the chi-squared distribution with one degree of freedom (Wald & Wolfowitz, 1940).

3. Results

3.1. Approach-1

One hundred and twenty-eight daily movements were estimated for period 1, 132 for period 2, and 2743 travel speeds for period 3. The mean straight-line DR values for each period were: 2.91 Km·day^{-1}± 0.24, 1.96 Km·day^{-1}± 0.17, and 6.19 Km·day^{-1} ± 0.03, respectively. After applying the tortuosity-related correction factor (6.40 for period 1, 8.78 for period 2, and 2.19 for period 3, Rowcliffe *et al*., 2012), the following corrected DRs were obtained: 18.62 Km·day^{-1}± 2.91 for period 1, 17.21Km·day^{-1}± 2.24 for period 2, and 13.55Km·day^{-1}± 0.56 for period 3.

3.3. Approaches 2 and 3

The activity indices and travel speeds estimated using the CT data are shown in Table 2. The activity patterns are shown in Fig 3. The average speed for moving behaviour is greater than that obtained for feeding (Table 2). In photo mode, 212 individuals were recorded in 149 passages. A DR of 4.93Km·day^{-1}± 1.02 (approach-2.1) and a weighted DR of 12.74 Km·day^{-1}± 1.89 (approach-3.1) were obtained from these data. In video mode, 141 individuals were recorded in 102 passages. The video data produced a DR of 3.01 Km·day^{-1}± 1.06 (approach-2.2) and a weighted DR of 14.00 Km·day^{-1}± 2.13 (approach-3.2).

299 Pairwise comparisons of the DR estimates between approaches showed only
300 statistically significant differences ($p<0.05$) as regards the DR values obtained from
301 approaches 2.1 and 2.2 and the other approaches tested (Fig. 4).
302
303 **4. Discussion**
304 We have revisited the approach by Rowcliffe *et al*. (2016) and we weighted by the
305 behaviour the formula with which to estimate the DR based on CT data. We have done
306 this by considering the results obtained in the same population monitored with telemetry
307 devices as a reference value (after applying the tortuosity-related correction factor) for
308 the DR. While the approach generally used to estimate the DR on the basis of CT data
309 (approach-2) notably underestimated the DR, the approach weighted by the behaviours
310 (approach-3) produced DR estimates that were coherent with those derived from
311 telemetry data, after correction with the tortuosity factor.
312 The problem of underestimating the DR from telemetry data is well known (Rowcliffe
313 *et al*., 2012; Alexander & Maritz, 2015; Sennhenn-Reulen *et al*., 2017) and have been
314 evidenced again in this work. The DR values estimated through approaches 1 & 3 are
315 around 15Km/day. Although these results are very different from those usually obtained
316 for wild boar (e.g. Spitz & Janeau, 1990; Podgórski *et al*., 2013), it can be explained
317 based on the fact that most of these studies considered straight-line distances between
318 consecutive locations obtained in telemetry studies. These studies, even it can be very
319 useful to compare animal behaviour between different situations (e.g. Podgórski *et al*.,
320 2013), are limited in the accurate of the results obtained in relation with DR. To our
321 knowledge, there are no studies that have been estimated the “real” DR of wild boar.
322 Camera-traps have been proposed as a useful method with which to estimate
323 movement parameters in accordance with their higher spatial accuracy of a few
324 centimeters (Rowcliffe *et al.*, 2012, 2016; Dewhirst *et al.*, 2016). In this paper, we have
325 employed the data obtained from CT as a basis on which to obtain DR values equivalent
326 to those obtained by means of telemetry. However, we have developed a new approach

based on that described by Rowcliffe *et al*. (2016). In this respect, the DR estimates obtained by directly applying the methodology described by Rowcliffe *et al*. (2016) –approach-2– were significantly lower than those obtained with the maximum sampling frequency used on tagged animals, even though frequencies such as those used in this work underestimate the real value by 50% (Rowcliffe *et al.*, 2012). This evidences that approach-2 is not able to derive precise DR values, or at least not with species that have marked behaviours. With these species, it is necessary to estimate a particular travel speed and activity for each particular type of behaviour, and then derive weighted DR estimations. In this study, after working with wild boar, we have proposed two general behaviours: "moving" and "feeding". We will eventually be able to record other behaviour, such as that of rutting. Our classification is based on the precise speed for each type of behaviour, instead of ecological significance. The types of behaviour observed should, therefore, eventually be classified on the basis of their speed. Rapid movements should be included in the feeding group, and slow movements in the moving group.

Most of the species with which the original approach for estimating DR from CT data was previously implemented were carnivores and rodents (Rowcliffe *et al*., 2016). Carnivore feeding behaviour can be described as a succession of feeding bouts and relatively straight and rapid relocation movements towards patches offering new feeding resources (Getz & Saltz, 2008). These species are not often recorded feeding, showing that most of the captures appertain to animals in movement. In the case of rodents, their movement have been described (Dobly, 2001; Cook, Anderson & Schweiger, 2004) as a succession of straight movements following natural or artificial linear structures ("runways") to travel between zones with high availability of resources. This can be explained on the basis of the distribution of resources: while the distribution of carnivores' or rodents' food resources is very precise, ungulates have general and widely-distributed resources, and capturing individuals behaving in different manners is, therefore, more probable. For all of the above reasons, we propose that for those species that behave differently in front of the cameras, it might be necessary to apply the approach described

here in order to obtain precise estimations of the DR when using CT.

With regard to the estimates obtained from CT, no significant differences were found between photo and video modes. In this study, we have used the rapid-fire technology (i.e. time lapses between consecutive photos in the same series of less than one second) that allowed us to record the paths travelled by animals with great precision. We, therefore, suggest the use of photos rather than videos. This is principally because the trigger speeds and recovery times are generally longer in video mode when compared to photo mode (Rovero & Zimmermann, 2016; Nakashima *et al.*, 2018), and photo data can be processed more quickly than video data, which is one of the most time-consuming stages in CT studies (Steenweg *et al.,* 2017). But this is also because photos require considerably less memory than videos (Glen *et al.*, 2013). Moreover, the video data estimates were highly variable. This could be explained by the smaller sample size obtained. Even though photo and video cameras were deployed on the same tree/stick, they did not record the same passages. This could be explained by the fact that we have considered all passages below a distance of ten meters from the camera. Some authors who have evaluated the sensitivity of the camera have obtained an effective detection distance for wild boar of around 5-6 meters (Hofmeester *et al*., 2017). These results lead us to conclude that those wild boar that passed between five and ten meters in front of the camera may not have been detected by both devices on all occasions.

Moreover, we have included a cost-benefit analyses (Appendix 2) comparing CT and telemetry as methods for estimating DR. Telemetry (always corrected by tortuosity) can be recommendable if we are working only with one species and we are interested also in other parameters like habitat use, CT have other advantages. For example, we are able to estimate DR for more than one species, and other ecology parameters like species occupancy and richness or activity patterns. Moreover, the applicability of CT studies are continually improving (e.g. Tabak *et al*., 2018), and the method will be more efficient in the future. An especial situation where CT are highly recommendable is if we are applying the REM. In this case, the use of CT are mandatory to apply the REM, and

we can obtain all the parameters to estimate population density from the CT data, i.e. without the need from including other methods (e.g. telemetry).

Although, the variation in the movement behaviour of populations of the same species living in similar habitats could be minimal (Rowcliffe *et al.*, 2012), we recommend more studies for a better understanding of the variation in the DR between populations, habitats and seasons. Overall, the results reported here highlight the utility of the REM when estimating wildlife population density, since precise DR estimates can be derived from the CT and from the same survey used to estimate the trapping-rate or group size. But in this respect, animals' behaviour should be taken into account in order to derive precise measures of the DR. This study supposes a step forward as regards establishing the REM as a core tool for wild boar monitoring, for which the feasibility and reliability of traditional population monitoring methods are limited. Moreover, the movement behaviour of the species have a lot of relevance in other ecological studies (Morelle *et al*., 2015), for example, as predictors of some diseases dynamics (Podgórski, Apollonio & Keuling, 2018).

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631 **Table 1**. Summary of movement parameters estimated using camera-traps. Travel speed estimations
632 (average speed of travel while active) are based on the best-fit distribution selected on the basis of AIC.
633 Activity index estimates (proportion of time spent active) were calculated using the R package "activity"

Camera mode	Approach	Activity index (SE)	Travel speed $m \cdot s^{-1}$ (SE)	Speed distribution (ΔAIC)		Day range $Km \cdot day^{-1}$ (SE)
				Log-normal	Weibull	
Photo	General	0.361 (0.034)	0.158 (0.029)	6.76	0	4.928 (1.020)
	Weighted	0.150 [f] (0.014)	0.033 [f] (0.016)	3.01 [f]	0 [f]	12.740 (2.073)
		0.211 [m] (0.020)	0.632 [m] (0.075)	6.86 [m]	0 [m]	
Video	General	0.392 (0.039)	0.089 (0.030)	6.76	0	3.014 (1.064)
	Weighted	0.171 [f] (0.017)	0.072 [f] (0.019)	0 [f]	1.60 [f]	13.997 (2.404)
		0.221 [m] (0.022)	0.680 [m] (0.088)	0 [m]	3.21 [m]	

634 [f] feeding behaviour, [m] moving behaviour.

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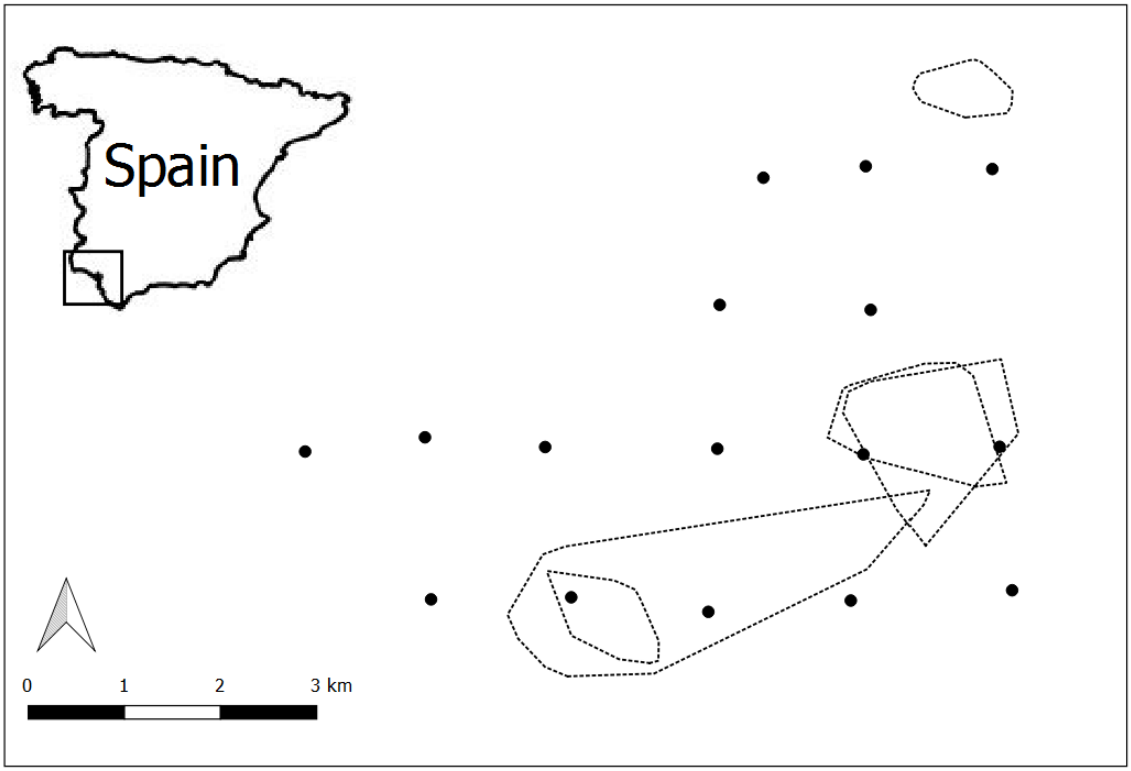

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639 **Figure 1.** Map of the study area. Camera-traps locations (black points) and home range of tagged

640 individuals in period 3 (dashed line).

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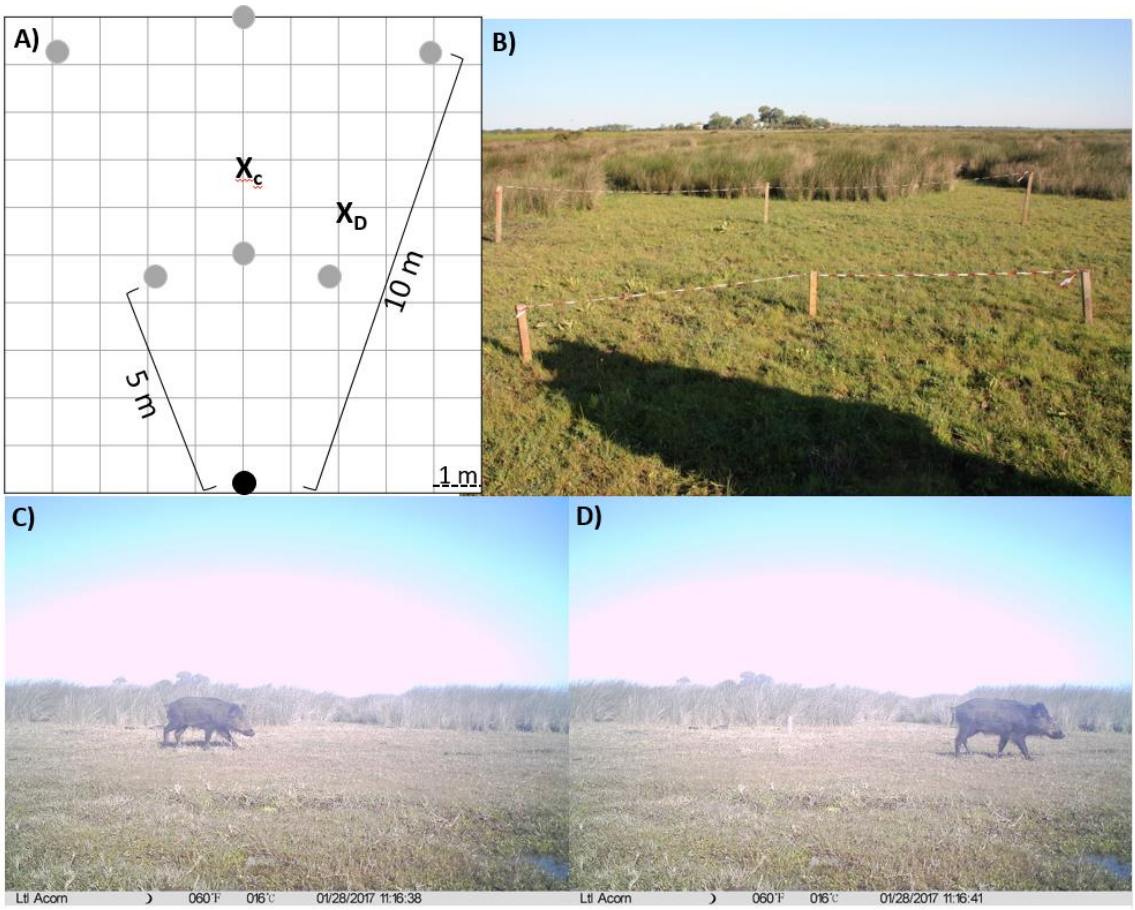
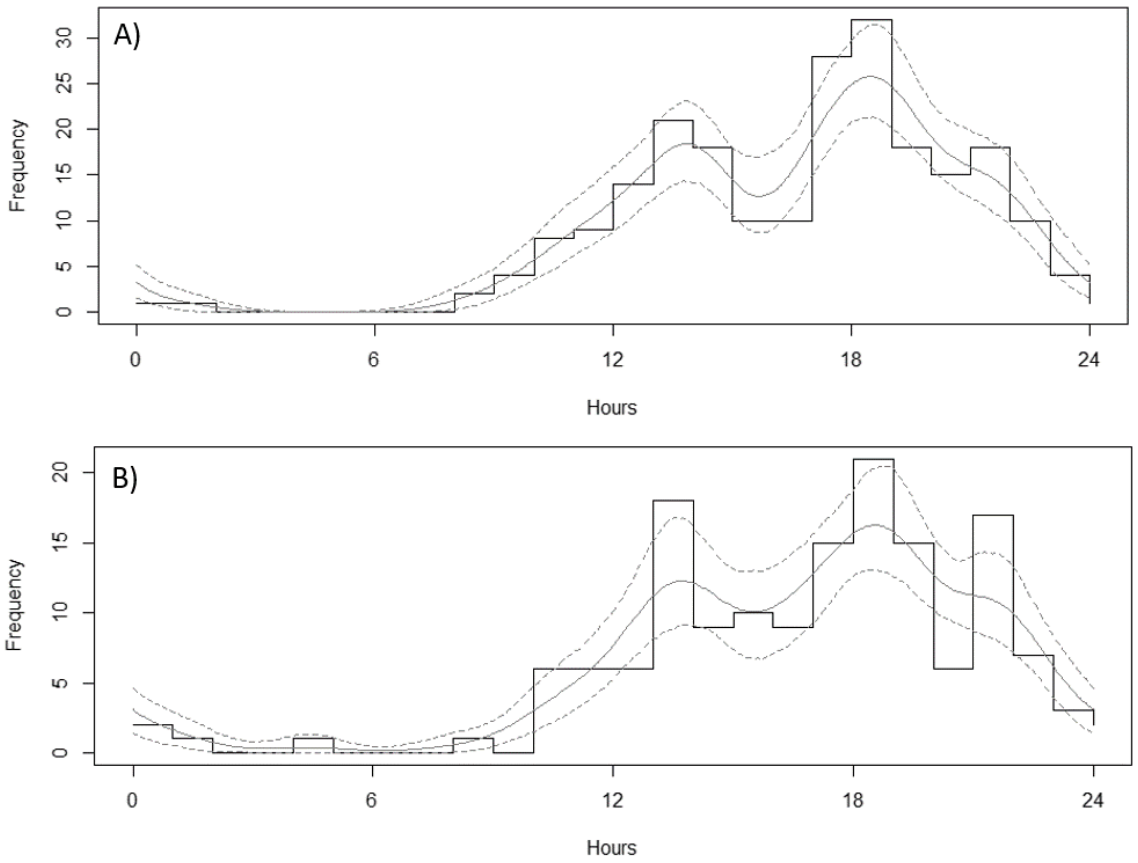


Figure 2. A) Scheme of the stick-structure (grey dots) used to reference the animals captured by the camera-trap (black dot). X_C and X_D indicate the position of the wild boar captured in images C and D, respectively. B) Photo of the structure installed at one photo-trapping sampling point. C) & D) Photographic sequence of a wild boar captured by the camera.



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655 **Figure 3.** Activity patterns of wild boar estimated from photo (A) and video data (B) using R package
656 "activity". Black steps are observed frequencies, grey curves are fitted kernel distributions and grey
657 discontinuous lines are SE.

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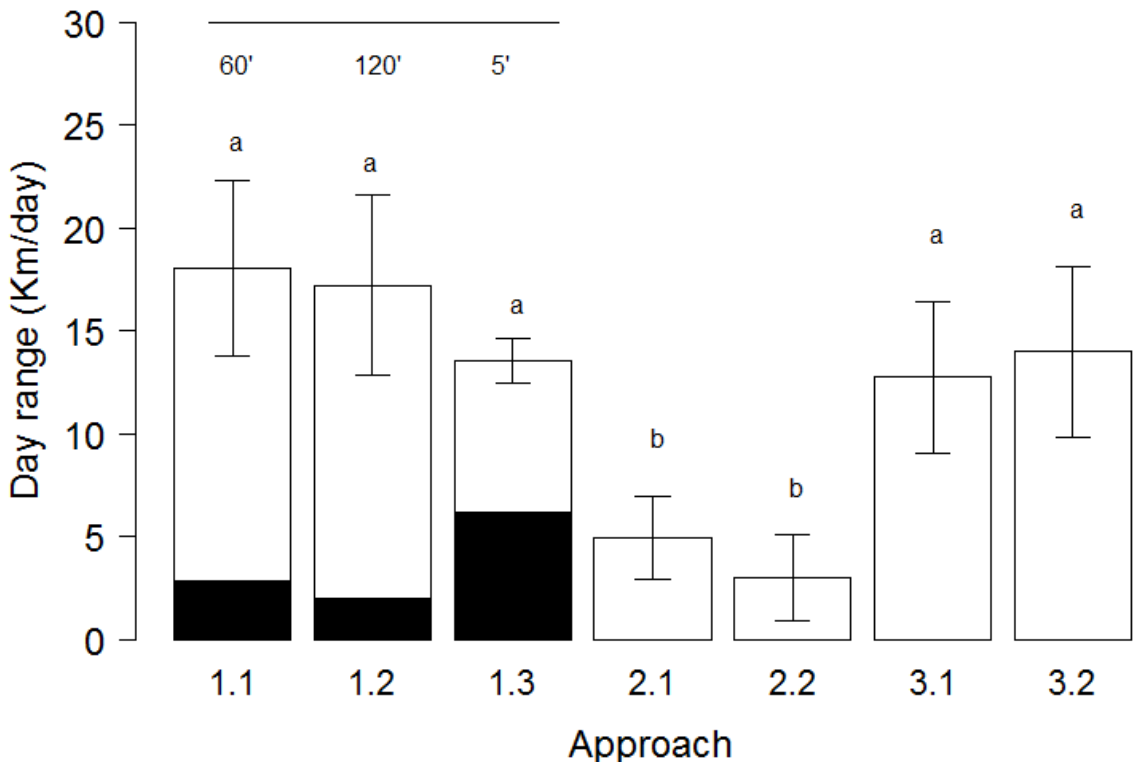

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664 **Figure 4**. Day range estimates obtained from: approach-1.1 to approach-1.3, telemetry data corrected by
665 tortuosity-related correction factor (Rowcliffe *et al.*, 2012) corresponding with the periods 1, 2 and 3
666 respectively; approach-2.1, general estimation based on camera-trap photos; approach-2.2, general
667 estimation based on camera-trap videos; approach-3.1, weighted estimation based on camera-trap photos;
668 approach-3.2, weighted estimation based on camera-trap videos. Upper axis indicates time lapse between
669 consecutive locations (in mins) in telemetry data. Lower black bars in telemetry estimates correspond to
670 straight-line estimates and upper white bars are the tortuosity-related correction in approaches 1.1-1.3.
671 Different letters show significant differences among DR estimation based on pairwise comparisons with
672 Bonferroni correction (p<0.05) after Wald test analysis. Error bars are 95% confidence intervals.

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